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Supply-side network effects on mobile-source emissions

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ABSTRACT

Mobile-source emissions are pivotal in quantifying the negative externalities of surface transportation, such as environmental pollution and climate-change, and in evaluating low-carbon traffic strategies. In such assessments, it is important to avoid prospective policy shortcomings. Hence, a wide range of sensitivities of mobile-source emissions must be understood, particularly from a traffic modeling standpoint. This paper takes a step in that direction and explores the effects of certain supply-side network attributes on emissions. Three key elements are investigated: level-of-detail of traffic activity, link speeds in the network, and link lengths. Both aggregated (hourly) and fine-grained (per-second) traffic activities are modeled using a simulation-based dynamic traffic assignment tool. Emissions are modeled using US Environmental Protection Agency's Motor Vehicle Emissions Simulator (MOVES). System-wide estimates of five criteria pollutants (CO, NO2, PM10, PM2.5, and SO2) and greenhouse-gases (CO2) are developed for a weekday morning peak-hour modeling period. Numerical experiments on a rapidly growing county in Central Texas, US, indicate that emission estimates are sensitive to all the aforementioned supply-side variables. Most notably, median network-wide estimates are found to increase in magnitude with aggregation of traffic activity and speeds. Effects of link lengths appear to be more prominent in high-speed traffic corridors, such as restricted-access highways, than low-speed unrestricted-access arterials. The latter, however, witness more traffic dynamics and subsequently contribute more to deviation in emission estimates across levels-of-detail. The findings highlight the need to be mindful of such physical sensitivities of emissions while enacting policy decisions, which frequently rely on network-based regional emissions inventories.

1. Introduction and background

1.1. Transportation emissions and relevance in global environmental regulations

Transportation systems are major contributors to air pollution, leading to vehicular or "mobile-source" emissions. According to the United Nations Framework on Climate Change Convention, 27% of the total US greenhouse gas (GHG) emissions in 2010 belonged to the transportation sector. Within the European Union, road transport is responsible for approximately 20% of all carbon dioxide emissions, with passenger cars contributing 12%. Vehicle emissions are also a political issue in most developed nations across the world, particularly considering the 1997 Kyoto Protocol, which set binding targets on GHG emissions. Rising concerns about the negative environmental externalities of transportation activity and development have spurred governments worldwide into assessing the environmental impacts of transportation projects prior to their procurement and implementation. Several efforts are currently underway to reduce both mobile-source GHGs to mitigate climate disruption. Several studies have also highlighted the pollutants other than GHGs, such as Gurjar et al. (2008) who analyze concentrations of total suspended particles, sulfur dioxide (SO_2), and nitrogen dioxide (NO_2) and their harmful impacts in several megacities across the world. Recent findings by the International Council on Clean Transportation (ICCT) indicate NOx emissions from modern diesel cars sometimes exceed up to 15 times the current regulatory limit in Europe, with some car manufacturers meeting diesel NOx emissions standards under more realistic driving conditions, and others failing those standards (Yang et al., 2015).

However, enabling low-carbon and sustainable transportation strategies requires more than just policy directives and multilateral dialogue. They require analytical frameworks to actually quantify and assess the environmental impacts. Mobile-source emissions estimation models lie at the heart of development of such global policies and

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regulations. Contemporary examples include the following: Transportation Conformity Rules and US Environmental Protection Agency (EPA)'s National Ambient Air Quality Standards (NAAQS) in the US context (Clean Air Act Amendments, 1990), European Union's emissions legislations on passenger cars and light commercial vehicles, and several other transportation emissions regulations set by global entities such as the Intergovernmental Panel on Climate Change (IPCC). Mobile-source emissions models, thus, often provide technical and strategic support to state, national, and international agencies, and serve a variety of policy directions.

At this juncture, it thus becomes critical to explore the sensitivities and dependencies of such models and emission estimates in as much depth as possible. Frameworks that regularly deploy these models hold keys to exploring such additional characteristics.

1.2. Mobile-source emissions practice

In common practice, mobile-source emissions analysis requires unification of models from the transportation planning and air-quality domains. Emissions estimation typically entails the following procedures: (1) quantification of traffic activity and traffic volumes, typically using travel demand or microsimulation models; (2) computation of associated emission factors using emission models; and finally, (3) combining the two models to obtain emission estimates. Therefore, developing accurate emission estimates is, thus, dependent not only on the individual accuracy of the two modeling exercises, but also on the "consistent and seamless interface and interdependence" among them (EPA, 1996). The current study deepens the understanding of the interactions between traffic dynamics and emission estimates.

Mobile-source emissions have also been shown to be directly impacted by traffic dynamics such as vehicle speed, acceleration, stops, starts, and operating cycles. Geographic and network-based attributes may also be perceived to have impacts on emissions; however, those impacts have not been sufficiently investigated in the literature. The next step in the evolution of the sustainable transportation toolbox and low-carbon traffic strategies is to integrate traffic dynamics with emissions modeling, and empirically examine the sensitivity of emissions to supply-side characteristics. This paper is a step forward in that direction.

1.3. Contribution statement

The key feature of the study is, thus, the development of new analytical strategies to examine the interaction of emissions with certain supply-side network data. Three key supply-side variables are currently explored: level-of-detail of traffic activity, speed-based classification of network links, and link lengths. By no means these represent the complete array of supply-side attributes, as there are several other roadway features encountered in practice. However, these represent the bare-minimum attributes for building a typical transportation network as part of conventional demand models developed in practice. They are, thus, the building-blocks of the supply-side network. Furthermore, these variables also synchronize well with the emissions model output.

Traffic activity is modeled using a simulation-based dynamic traffic assignment (SB-DTA) tool called "VISTA" (Visual Interactive System for Transport Algorithms) (Ziliaskopoulos and Waller, 2000). Emission estimates are produced using the US-EPA regulated Motor Vehicle Emissions Simulator (MOVES), which offers the capabilities of fine-grained emissions modeling at the level of individual network links. The core of the modeling effort, thus, includes integrating MOVES with DTA at multiple levels of detail or resolutions of vehicle activity, which becomes valuable in exploring the sensitivity of emissions to level-of-detail of traffic. Two model components are developed: the link data average (LDA) model and the link drive schedule (LDS) model. LDA considers aggregated or average link data, whereas LDS contains per second vehicle activity on links. The integrated framework containing both these models can enable stakeholders and agencies to develop more exhaustive emissions inventories. Apart from exploring minute sensitivities of link-level emissions, the study also produces opportunities to leverage more advanced planning models containing the DTA engine.

The specific contributions of the study span across both academic research and industry practice and can be articulated from various perspectives, which are noted as follows:

Methodological: Unlike microsimulation models that generally perform dynamic network loading, the current DTA model rests on the principle of dynamic user equilibrium (DUE). DUE predicts vehicle route choice under the assumption that individual vehicles choose routes to minimize their travel time and costs, and thus better characterizes driver behavior.

Practical: It advances the current state of practice by providing a mobile-source emissions modeling package with potential applications ranging from local test-beds, such as short corridors or signalized intersections, to reasonably large-sized transportation networks that may represent region-wide air-quality analysis areas.

Versatility: The combination of LDA and LDS models is versatile as it can be tailored according to availability of resources. Different modeling scales highlight their respective nuances in terms of input data requirements and computational effort. Agencies may not always have access to detailed and flexible traffic models such as mesoscopic DTA, and may sometimes also face computational challenges in managing high-fidelity traffic data. In such circumstances, they may choose an LDA-type model approach or even use their conventional macroscopic or static models. A sensibility regarding the potential impacts of such choices on resultant emission estimates can be a critical factor in policy decisions. The combination of LDA and LDS models, thus, reflects a range of policies and modeling practices that may be adopted by planning agencies.

The remainder of this paper is, thus, organized as follows. Section 2 conducts a literature review of related previous studies; Section 3 briefly discusses the relevant modeling aspects including the MOVES emissions estimation methodology, the integration with VISTA DTA, and the LDA and LDS models. Section 4 demonstrates a numerical application on a real-life study area of Williamson County, Texas (US). It also analyzes the observations therein, and develops practical and policy insights. Section 5 concludes the paper by summarizing the work and developing future research avenues.

2. Literature review

Several factors potentially affecting vehicle emissions have been explored in the past. In terms of traffic operations, several factors have been studied including congestion (Andre and Hammarstrm, 2000), driving behavior (Vlieger et al., 2000, Hallmark et al., 2002, LeBlanc et al., 1995), route choice of motorists (Ahn and Rakha, 2008), traffic signals (Rakha et al., 2007), and junction effects (Hallmark et al., 2002; Matzoros, 1990). Qu et al. (2003) assert that road design features such as grade, alignment, and quality and their influence on driving patterns can affect emissions. Nesamani et al. (2007) highlight emission impacts of additional dynamic variables such as roadway, weather, and driver characteristics. Summala and Kilpelaninen (2004) shed light on effects of weather-related attributes such as temperature, humidity, and visibility on emission estimates, both by way of influencing driver behavior and chemical reactions with certain primary chemical pollutants.

Traffic simulation models have often been used to incorporate traffic-related factors into the emission modeling process. These models can capture traffic-related effects in ways better than were possible through earlier high-level planning models. Some of the prior integration attempts include traffic micro-simulation model VISSIM and comprehensive modal emission model (CMEM) (Stathopoulos and

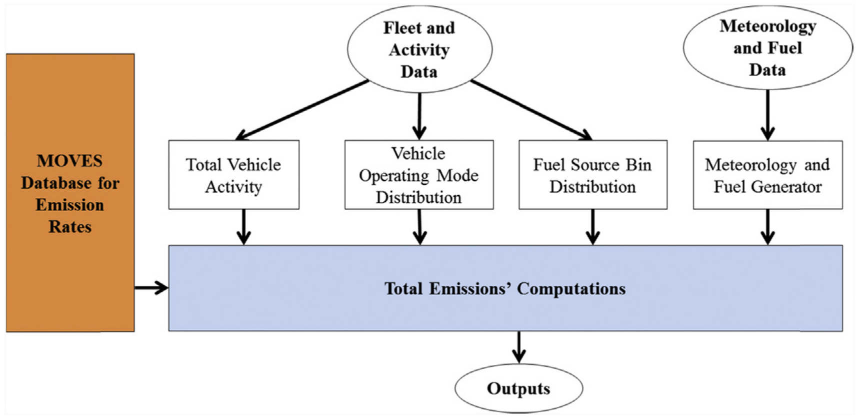

Fig. 1. MOVES emissions estimation flowchart.

Noland, 1842; Noland and Quddus, 2006), VISSIM and MOVES (Abou-Senna and Radwan, 2013; Abou-Senna et al., 2013), microscopic DTA model DynusT and MOVES (Lin et al., 2011), and PARAMICS and MOVES for evaluating emissions from alternately fueled vehicles (Xie et al., 2012). Research has explored impacts of considering average speed distributions over mean speed values (Smit et al., 2008; Beek et al., 2007) and impacts of static versus dynamic traffic assignment models in emission estimation (Wismans et al., 2013). Zhao and Sadek (2013) investigate computationally efficient approaches for integrating MOVES with microscopic traffic simulators. Most recently, Fontes et al. (2015) present directions in using microsimulation tools for assessing environmental impacts of traffic, and also cover a more comprehensive synthesis of the integration of traffic, emission, and air-quality models.

Recognizing the contributions of previous studies, the current study is nonetheless different and unique in various ways. First, the traffic modeling approach is not a microsimulation model but a DTA model built on equilibrium (DUE) principles that identify system conditions over a longer planning horizon. Microsimulation models are typically not designed to explore the long-term strategic behavior of drivers that leads to system-wide recurrent traffic conditions. They are more suited for evaluating relatively short-term and localized corridor-based traffic flow patterns, and have yet to become conveniently applicable to region-wide planning networks. Second, from the standpoint of applicability, it is also designed to be more closely relevant to regional transportation planning and macro-level policy analyses. The DTA-based emissions package could also be a better trade-off between computational complexity and practical usability than existing frameworks.

3. Methodology

This section briefly discusses the relevant computational aspects of both MOVES and the VISTA DTA model used in this study. It also discusses the development of the LDA and LDS models.

3.1. MOVES emissions estimation

MOVES incorporates instantaneous speed profiles on emissions, and is capable of conducting emission analysis at various spatial scales. The project-level scale of modeling in MOVES is the most fine-grained and appropriate to leverage the high-fidelity traffic data offerings of a DTA platform. Within this scale there are further choices of either hourly average data, or per-second LDSs, and even per-second operating mode distribution, each one degree finer resolution than the previous. Open choices regarding scale of modeling make it suitable to investigate the effects of level-of-detail being supplied.

For computation of emission estimates, MOVES uses a “modal” approach such that emission factors are based on operating modes of vehicles. Operating modes are functions of vehicle speed, acceleration, and road grade. Operating mode information is stored in the form of bins that are created based on second-by-second speed information and a metric called vehicle specific power (VSP) (Jimenez et al., 1999). A more analytical description for VSP and their use in developing LDSs will be covered in a later subsection. More comprehensive descriptions of the MOVES emission estimation methodology can be found in literature such as Vallamsundar and Lin (2011) and the user documentation by EPA (2012). In summary, some notable capabilities of MOVES relevant to this study include the following: a multi-modal binning approach to emission estimation driven by dynamic variables of traffic such as speed, acceleration, and road grade; flexible spatial and temporal resolutions; and broad coverage of various geographical-scales. In addition to vehicle activity input data, certain area-specific data are also included, which helps tailor emission estimates to conditions of the study-area. They include source-type age distribution (containing an estimate of the age characteristics of the vehicle fleet in the region), meteorology data (describing temperature and humidity conditions of the area being modeled), and fuel-supply and fuel-formulation (covering all possible categories of fuels used by local vehicle fleets along with their chemical compositions).

The following flow-chart (Fig. 1) summarizes the emissions estimation process in MOVES, also indicating the range of input variables and their use.

3.2. Mesoscopic DTA modeling and VISTA

The current study adopts mesoscopic-level DTA, which is a bridge between regional planning-level macroscopic models and localized microscopic models. The mesoscopic scale traffic model is a middle ground between the macroscopic scale, which may risk loss of essential detail by aggregation, and the microscopic scale, which simulates individual vehicles, and is computationally prohibitive for larger regions. Mesoscopic DTA simulates traffic patterns at a sub-regional or corridor level, including traffic dynamics such as congestion growth and dissipation, driver rerouting, and queue spillovers at fine temporal and spatial resolutions. More discussion on practical features of DTA can be found in Chiu et al. (2011).

Mesoscopic DTA modeling is an effective way to model traffic dynamics at larger geographical scales than is practically possible by microscopic simulation models. At the same time it enables a more detailed estimation of traffic flow than macroscopic models. DTA thus provides a detailed and coherent means to represent the interaction between regional transportation demand, motorist-route choice behavior based on their experience, and anticipation of network traffic conditions and vehicle flows. Chiu et al. (2011) also assert that it captures the inherent user behavior of minimizing the travel costs. DTA uses the notion of “experienced” travel times where the users are

assumed to be aware of the network conditions based on their experience, and use that knowledge to choose an optimal path. It is also an improvement over the hitherto conventional static traffic assignment models. Static models are essentially a time-of-day approach (a more aggregated time window), which provide an average estimate of flows through inherently assumed steady-state behavior, but without much insights into congestion locations and times, vehicle queue formations and spillbacks. They may also lead to an inadequate representation of over-saturated network conditions. These are some factors that can have significant impacts on vehicle emission dynamics, as vehicle operating modes alternate rapidly during congestion, and so do the emission rates of pollutants.

Drivers' route choices depend on their perceived travel times, but travel times for the system, in turn, depend on route choices of all drivers. To capture this feedback loop, DTA applies an iterative methodology that converges when drivers' perceived travel times and the resultant route choices become consistent with each other. This denotes a user-equilibrium solution in which no driver can unilaterally reduce their travel time by switching their paths. As mentioned earlier, the underlying principle is DUE, which states that all trips between the same origin and destination, and departing in the same time period, have approximately the same travel cost. The users or drivers in the system are assumed to be aware of prevailing network conditions, while exhibiting rational time and cost-saving behavior. The user equilibrium approach replicates real-life choices and network conditions more effectively, and is adopted in the current study. However, impacts of using other assignment algorithms on emissions remain to be seen and could be worth exploring in future research.

In order to meet the DTA modeling needs for this study, the VISTA modeling framework is used. It integrates spatio-temporal data and models for a wide range of transport applications in planning. VISTA's traffic propagation modeling approach is based on the cell transmission model (CTM), originally proposed by Daganzo (1994, 1995). VISTA is a simulation-based DTA model, and is web-based and platform-independent. More technological insights into the VISTA platform can be found in Ziliaskopoulos and Waller (2000).

3.3. The LDA model

The LDA model concerns with the average vehicle speeds and volumes on every link in the network. MOVES then assigns a default operating mode distribution based on typical default driving cycles. Despite the reliance on MOVES' default distributions, this input nonetheless accounts for the heterogeneity across individual links in the network and conveys important link-specific data that are summarized below.

First, for each link, this model specifies the class of roadway the link belongs to, reported in the form of a MOVES road-type classification. In this study, link speed characteristics are used to determine the roadway class of the link. Links with higher free-flow speeds ($\geq$55 mph) are classified as "urban restricted access", which represent freeways and expressways for high-speed traffic. Links with lower free-flow speeds are classified as "urban unrestricted access," representing arterials, smaller streets, or local corridors. Once the DTA network links are classified based on MOVES road-types, the link length (in miles) and the average hourly traffic volume on the links (in vehicles per hour) are also computed from the DTA model output for the peak hour simulation period. Link lengths are a standard attribute of links. The average traffic volumes cover the total traffic flow across all vehicle types during the modeling hour (AM or morning peak in this case). A relatively much finer time-interval traffic assignment output is provided by the DTA model; hence, data aggregation is employed to produce their hourly averages. Average link speeds are computed based on the average time spent by the vehicles using the link and the link lengths.

Another important link attribute that is computed is the average road grade (inclination). Road grade has been found to influence energy consumption (Levin et al., 2014) and vehicle emissions (Cicero-Fernández et al., 1997; Park and Rakha, 2006). Under the integration approach in this study, the elevations of the start and end points of a link and its length are used to determine the grade. Elevations of nodes are determined from their geographical co-ordinates, which are mapped on the Google Maps API to provide the corresponding elevation data.

In summary, this subset of the integration model requires an aggregated level-of-detail that can be obtained with relatively lesser effort than per-second data such as drive schedules. Qualitatively, this model choice also represents a scenario where agencies may utilize average link attributes due to lack of access to high resolution traffic data, or even in cases where more computational effort is not feasible due to time and resource constraints. That being said, average link speeds and traffic volumes are the minimum data that are requisite for project-level modeling, beyond which MOVES can invoke its own default drive schedules.

Despite being lower resolution than the LDS model, which will be covered in the next subsection, LDA is yet an effective mechanism of providing computationally faster and initial estimates of aggregated area-wide emissions. But LDA may be inadequate in fine-grained analysis, and also in fully leveraging the offerings of microsimulation or DTA models.

3.4. The LDS model

The LDS model is more fine-grained than the LDA model and provides the opportunity to input link speed and grades as a function of time (in seconds) on a particular roadway link. Typically, MOVES uses real-world drive schedule data as its defaults. Emissions are computed in a way that a wide range of possible driving patterns and their resultant emissions are considered. From the mesoscopic DTA model assignment output, vehicle flows per link, vehicle path, and route choices, and travel time information is extracted and postprocessed to provide MOVES with second-by-second speed data to generate customized drive schedules. These data are then used by MOVES to calculate the second-by-second VSP, briefly mentioned earlier. VSP, along with vehicle type and vehicle age and several other supply-side variables, is used to allocate emission factors or rates. These factors are applied in proportion to the relevant vehicle activity data to generate final emission estimates inventories for the area or network under consideration. This workflow may repeat based on the number of pollutants being modeled, given unique emission rates for each pollutant.

In sum, emission estimates are based on real-world driving as much as possible. Based on the DTA-based LDS supplied, MOVES builds its own vehicle operating mode distribution to estimate the emissions. Operating modes represent the fraction of total travel time spent within different possible vehicle activity conditions including braking, idling, coasting, cruising, and accelerating within various speed ranges and VSP levels (Abou-Senna and Radwan, 2013). As briefly mentioned earlier, the modal binning approach stores the operating mode information and is associated with the VSP. A mathematical definition of VSP is worth discussing here. VSP is an estimate of the power demand on the engine during driving, and is calculated using per-second speeds from the drive schedule, along with information on the type of vehicle. VSP is used by MOVES to determine the amount of time a vehicle spends in each of its different operating mode bins. For each drive schedule mapped, VSP (units kW/tonne) is computed using the following relation:

$$VSP = v(a(1+\varepsilon) + g\phi + gC_R) + \frac{2\rho C_D A v^3}{m} \tag{1}$$

where.

v = speed of vehicle
a = vehicle acceleration (m/s^2)

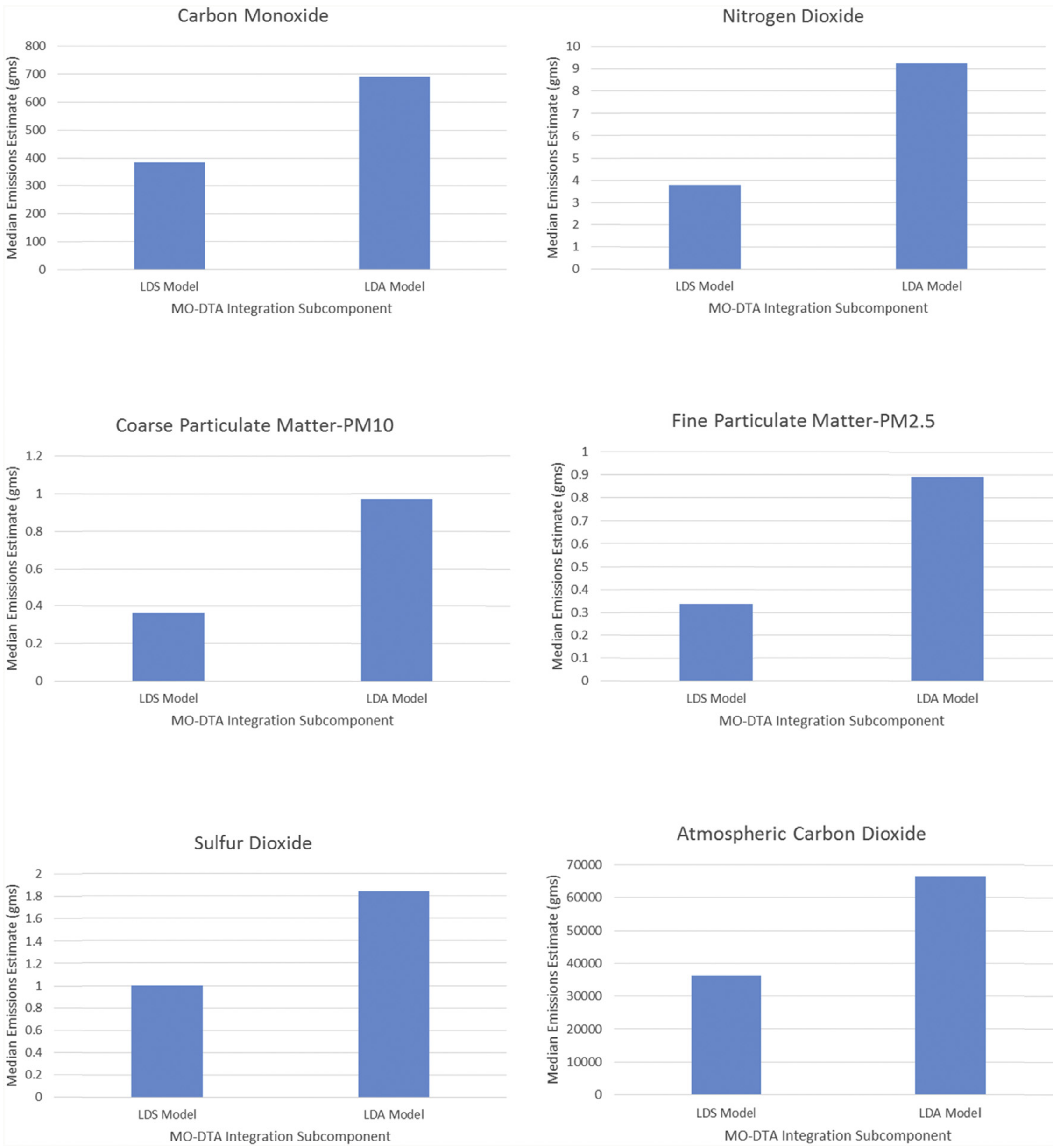

Fig. 2. Median emission estimates for key criteria pollutants and GHG (gms/link).

ε = rotational mass factor
g = acceleration due to gravity (9.8 m/s^2)
ϕ = road grade
C_R = rolling resistance coefficient
ρ = density of air
C_D = aerodynamic drag coefficient
A = vehicle frontal area
m = vehicle mass

The modal approach then estimates VSP values for every discrete operating mode, and modal average emission rates are estimated for each mode. The total emissions during the course of a trip are estimated by the following relation:

$$E_{trip} = \sum_{i}^{I} T_i^{VSP} ER_i \tag{2}$$

where.

i = index representing a specific VSP operating mode
I = total number of VSP operating mode bins
ER_i = modal average emission rate for VSP mode i
T_i^{VSP} = time spent in VSP mode i
E_{trip} = total emissions during the trip

Thus, it can be observed that VSP is a single unifying factor that links vehicle-based traffic dynamics and activity to network-based emission rates. VSP is a generic metric, which can be computed for different vehicle-types using their relevant parameters. The ease at which physical characteristics can be represented, and its strong statistical correlations with vehicle emissions makes the VSP-approach a widely followed method in emissions estimation (Fontes et al., 2015).

For the VISTA mesoscopic DTA approach, each vehicle is simulated and traced in the network, and network conditions and flows are updated every 6 s. Trajectories of all vehicles during the simulation period are recorded. The drive schedule is, thus, created by mapping those trajectories with the link-type and the corresponding grade, at every second of the modeling hour for every link in the network. Under this fine-grained methodology, disaggregate speed values from the DTA

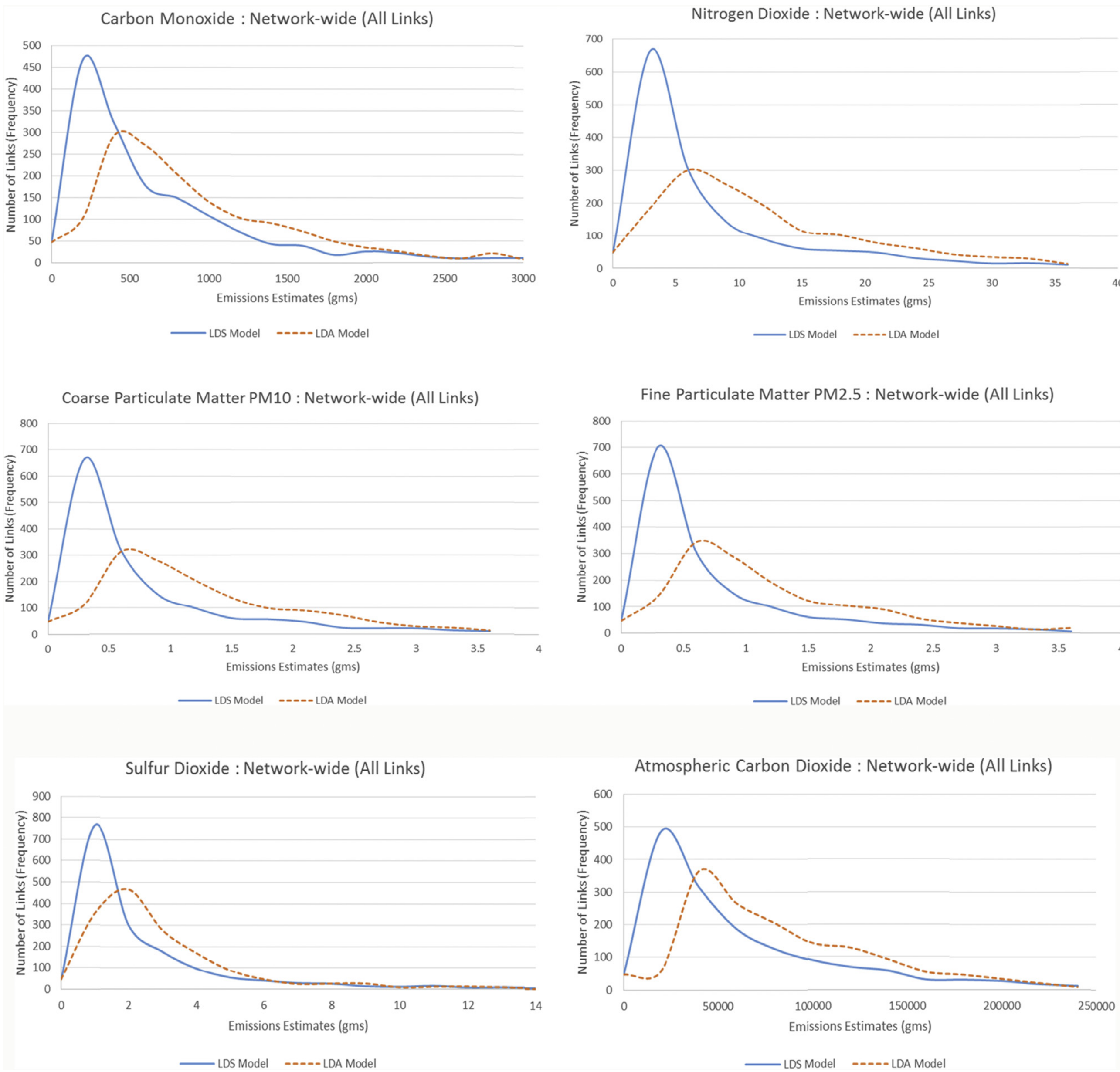

Fig. 3. Frequency distributions of link-level emission estimates.

model are used. In the current study, only a single vehicle type is considered (passenger car-type).

Qualitatively, the LDS model represents a scenario where the planning agencies (such as metropolitan planning organizations: MPOs) might have access to high-resolution vehicle activity pattern or per-second vehicle trajectory data, and/or the traffic model capabilities to generate such data. While microsimulation models have been used in several previous studies to develop such per-second inputs, it can be seen here that considering the link-level per-second data generation, they can easily become computationally prohibitive as network-size increases. This hinders their applicability to larger planning-level models. These practical challenges are overcome using a mesoscopic DTA-based traffic model platform where LDSs can be developed for relatively much larger study-areas with a wide geographical coverage.

It is also worth noting here that apart from the two above mentioned inputs (average link data and LDSs), a third category of inputs containing the operating mode distribution can also be inputted in MOVES. Under this input, the operating mode fraction data for source types, hour/day combinations, and pollutant/process combinations can be included, if available. However, MOVES guidance documents (EPA, 2012) report that if either the average speed or link-drive schedule approach is used, it is not necessary to input a separate operating-mode distribution for on-road link activity. Because only on-road running exhaust emissions are modeled in the present study, these inputs are not separately developed, and the default operating mode distributions produced by MOVES using the DTA-based drive schedule are used. Ultimately though, the decision to choose either the average link data, or the LDS, or even the operating mode distribution data relies on the resources available to the agency. The decision can also be made depending on the size and type of area being modeled, and the level of resolution warranted.

3.5. Computation of velocity and acceleration

As seen from the VSP model (Equation (1)), vehicle speed and acceleration are important inputs in the estimation of emission rates, and this section discusses the analytical methodology for computing these in the VISTA, the DTA simulator used in this study. Traffic flow is

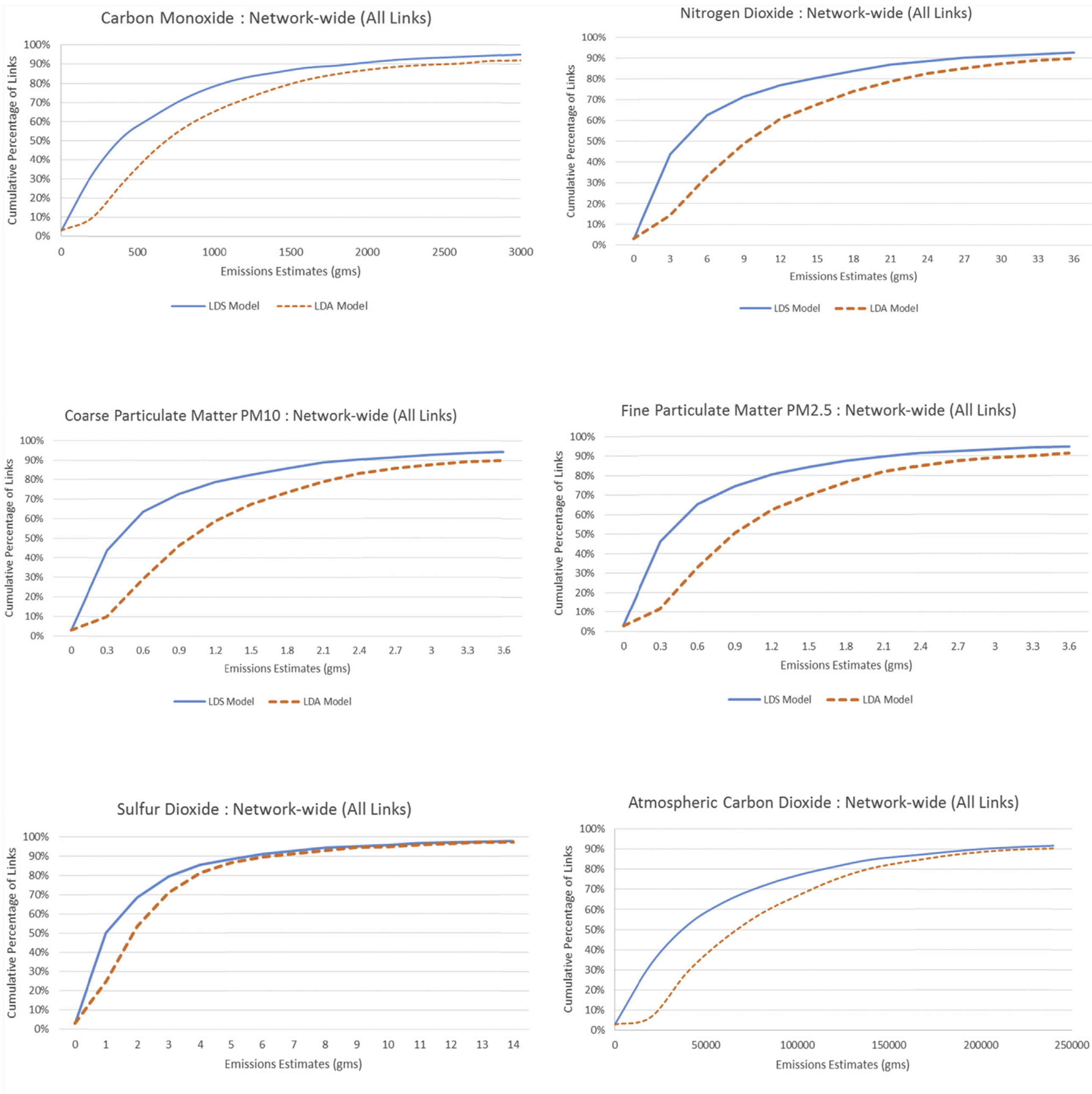

Fig. 4. Cumulative frequency distributions of link-level emission estimates.

discretized, and individual vehicles are tracked in the model, and VISTA's traffic propagation modeling approach is based on CTM as discussed earlier. As a first-order model, CTM does not explicitly output acceleration but provides link travel times per vehicle, which can yield the average speed experienced by the vehicle on the link. Although some traffic assignment models may output speeds at smaller spacing intervals, others, such as the link transmission model, do not contain enough information to do so. In this method, it is possible to approximate speed changes on a link when only information at upstream and downstream ends is given.

Average individual vehicle speeds are averaged to calculate the average speed of the link at a small time step of $\Delta t = 6$ seconds. Acceleration is calculated as the rate of change in average speed on links, and between links at intersections. Formally, let π_i be the path of vehicle i. For every link $e \in \pi_i$, let L_e be the length of e, θ_e be the gradient angle of e, $\tau_i^{\uparrow}(e)$ be the time i arrives on e, and $\tau_i^{\downarrow}(e)$ be the time i exits e. Then, vehicle i has an average speed on e, v_e^i, of

$$v_e^i = \frac{L_e}{\tau_i^{\downarrow}(e) - \tau_i^{\uparrow}(e)} \tag{3}$$

The average link speed at some time t is a function of the average individual vehicle speeds of vehicles on the link at t. First define the set $S_e(t)$ of vehicles on the link at t :

$$S_e(t) = \{i | e \in \pi_i \wedge \tau_i^{\uparrow}(e) \le t \le \tau_i^{\downarrow}(e)\} \tag{4}$$

Then, the average link speed at t, $\overline{v_e}(t)$, is the average of the individual vehicle speeds of vehicles in $S_e(t)$:

$$\overline{v_e}(t) = \frac{\sum_{i \in S} v_e^i}{|S_e(t)|} \tag{5}$$

Once the upstream and downstream speeds are known, the model assumes that in the last time step spent on e, i accelerates to $\overline{v_{e+1}}(\tau_i^{\downarrow}(e))$.

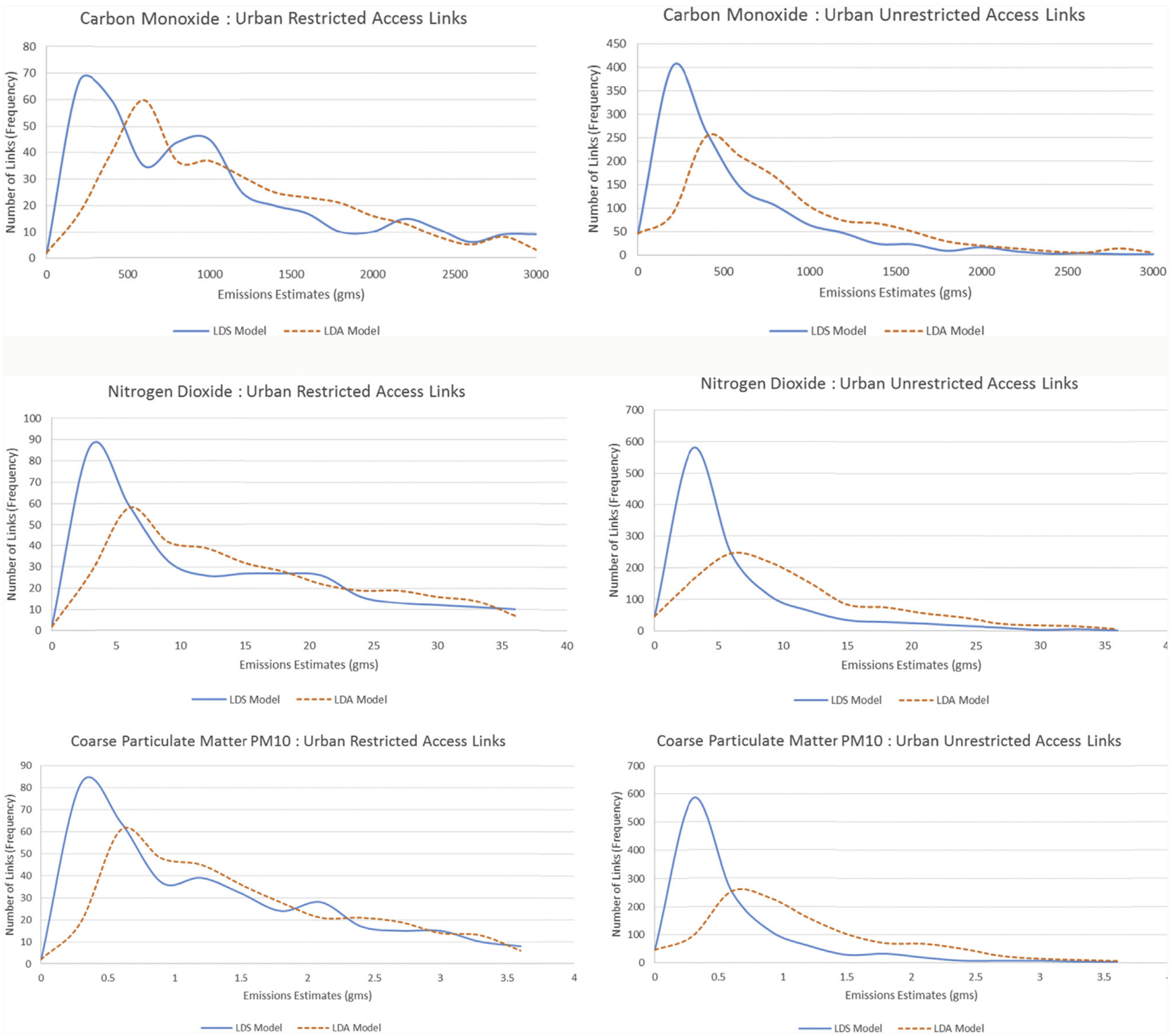

Fig. 5. Frequency distribution of emission estimates classified by road-type.

A more realistic instantaneous acceleration is difficult to determine from the first-order flow model output. Time spent idling at intersections is included in the difference between $\tau_i^{\uparrow}(e)$ and $\tau_i^{\downarrow}(e)$, and thus reduces the average link speed for the vehicle.

4. Case-study application and numerical experiments

This section discusses a real-life case-study application of the above developed framework containing the LDA and LDS models. It also covers relevant numerical experiments to examine prospective supply-side network effects.

4.1. Study area description and criteria pollutants

LDS and LDA models are now deployed to perform multi-resolution emissions modeling on the study-area of Williamson County near Austin, Texas. The Austin regional district in Central Texas is one of the fastest growing urban areas in the US, and the traffic and vehicle activity growth in the area has shown a commensurate increase. For the purpose of analysis, the morning peak-hour window (8 a.m.-9 a.m.) is chosen for both the DTA model and the MOVES model. The base network for Williamson County is a dense network with 1628 links, 961 nodes, 113 traffic analysis zones, and 66 signals. Across the entire network, more than half the links (approximately 72%) belong to the urban restricted access road-type (including limited access highways and expressways for high-speed traffic), whereas the remaining 28% belong to the urban unrestricted access road-type (including other corridors and local arterials). This distribution is mainly attributed to the suburban location of this county, coupled with passage of several major highways through it such as IH-35, US-183A, US-79, SH-130, among others.

The US-EPA has set ambient air-quality limits for six common air pollutants. These include some of the most commonly found air pollutants or aforementioned "criteria pollutants". Five such criteria pollutants are modeled in this study including carbon monoxide (CO); nitrogen dioxide (NO_2); coarse particulate matter with particle size 10 µm or less (PM10); fine particulate matter with particle size no greater than 2.5 µm, such as smoke and haze (PM2.5); and sulfur dioxide (SO_2). In addition to these, GHGs such as atmospheric carbon dioxide (CO_2) are also considered. Morning peak-hour emission inventories for all these pollutants are developed at two different resolutions using the LDS and LDA models. As mentioned previously, only running exhaust emissions from vehicles are considered. This practical application also presented some challenges in terms of data availability

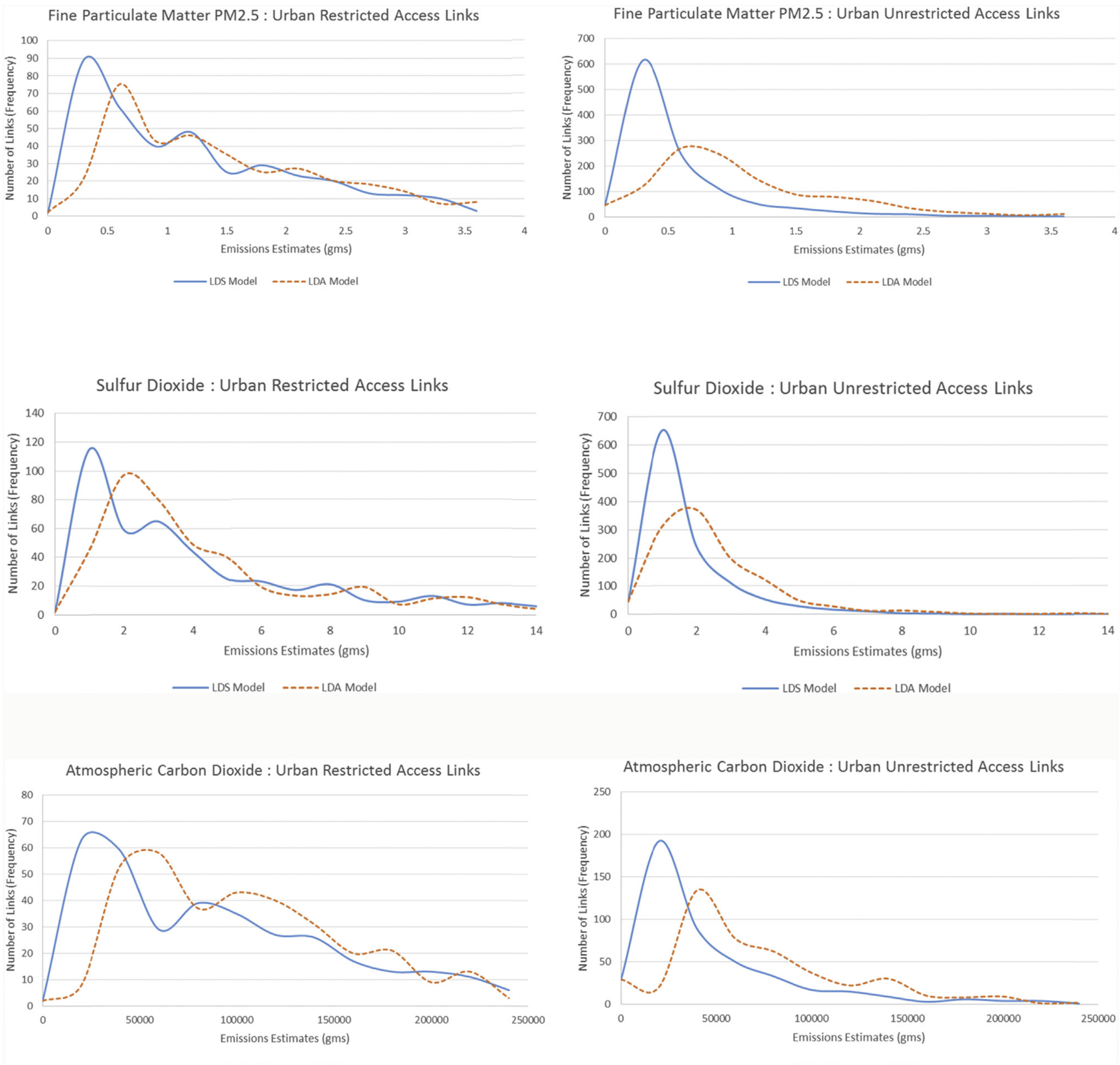

Fig. 5. (*continued*)

and computation. Regional data on vehicle fleet and activity, and meteorology and fuel inputs had to be procured from the local MPO. It is often time and resource-intensive to collect and maintain up-to-date records of such data. Fine-grained traffic activity as required especially by the LDS model also poses some computational and memory challenges. It is also contingent upon maintaining an up-to-date demand model for the region, along with the latest network attributes and trip matrices, and a reliable traffic assignment algorithm.

4.2. Network-wide emission estimates and distributions

Central tendencies of system-wide emission estimates obtained under the LDA and LDS models are computed here. Fig. 2 shows the median emission estimates over all links in the network, and a comparison of estimates across the two models.

It is noted that the median emission estimates are higher for the coarser LDA model than that of the relatively much finer LDS model. Aggregation of fine-grained data such as per second speeds and VSP into hourly averages under the LDA model is thus found to result in higher magnitudes of emission estimates. While median estimates may serve as a single system-wide performance measure as they are computed over the gross emissions inventory, the model provides link-level estimates which can be used to further examine the spatial distribution of emissions on links spread out across the network. To that end, frequency distribution plots (histograms) and cumulative distribution plots of pollutant estimates are developed considering all links in the network, as shown in Fig. 3.

It is observed that across all pollutants modeled in the study, distributions of emission estimates using either of the models are not symmetric but are skewed relative to each other. Given the right-skewness of both, there is no "center" of emission estimates in the usual sense of the word. Data with fixed lower bounds are often skewed right, and the current set of link-level emission estimates is also nonnegative, with a fixed lower bound of zero grams. Also for all pollutants, it can be seen that the mean emissions estimate value (with the maximum frequency of occurrence) is higher in the LDA model than in the LDS model. The distribution curve for the LDA model is also relatively flatter than that of the LDS model and with longer tails, indicating a

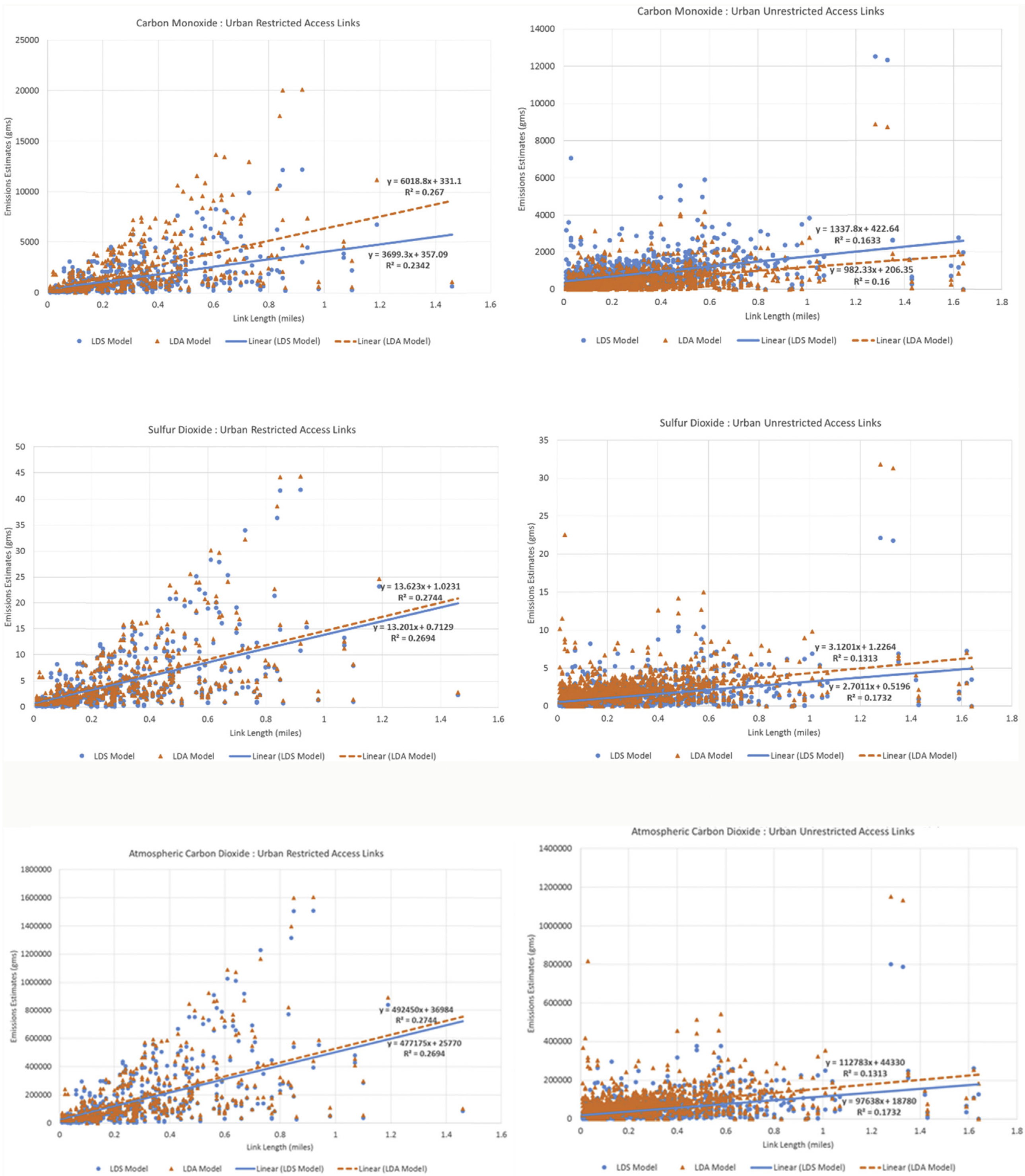

Fig. 6. Variations of emission estimates with link lengths along different road-types.

wider spread of relatively high-emission links across the network, once again consistent with higher median per-link estimates. These findings are further validated below, where Fig. 4 illustrates the cumulative distributions of the network-wide emission estimates.

The cumulative distributions for the LDA model are right-shifted to the higher side than that of the LDS model, indicating higher probabilities of encountering higher emission links throughout the network. Mathematically, this indicates a stochastic dominance of the LDA model over the LDS model in terms of network-wide emissions estimation. This indicates that in every possible state of the system, the LDA model outcomes (or emission estimates in this case) are higher than the LDS model. A strict stochastic dominance, however, is not observed for one criteria pollutant—SO_2 because at higher values of estimates, the cumulative frequencies (or percentage of links) are almost the same for both the models, and not necessarily higher for the LDA model. The dominance appears most prominent in NO_2, PM10, and PM2.5, especially through the low to mid ranges of emission estimates.

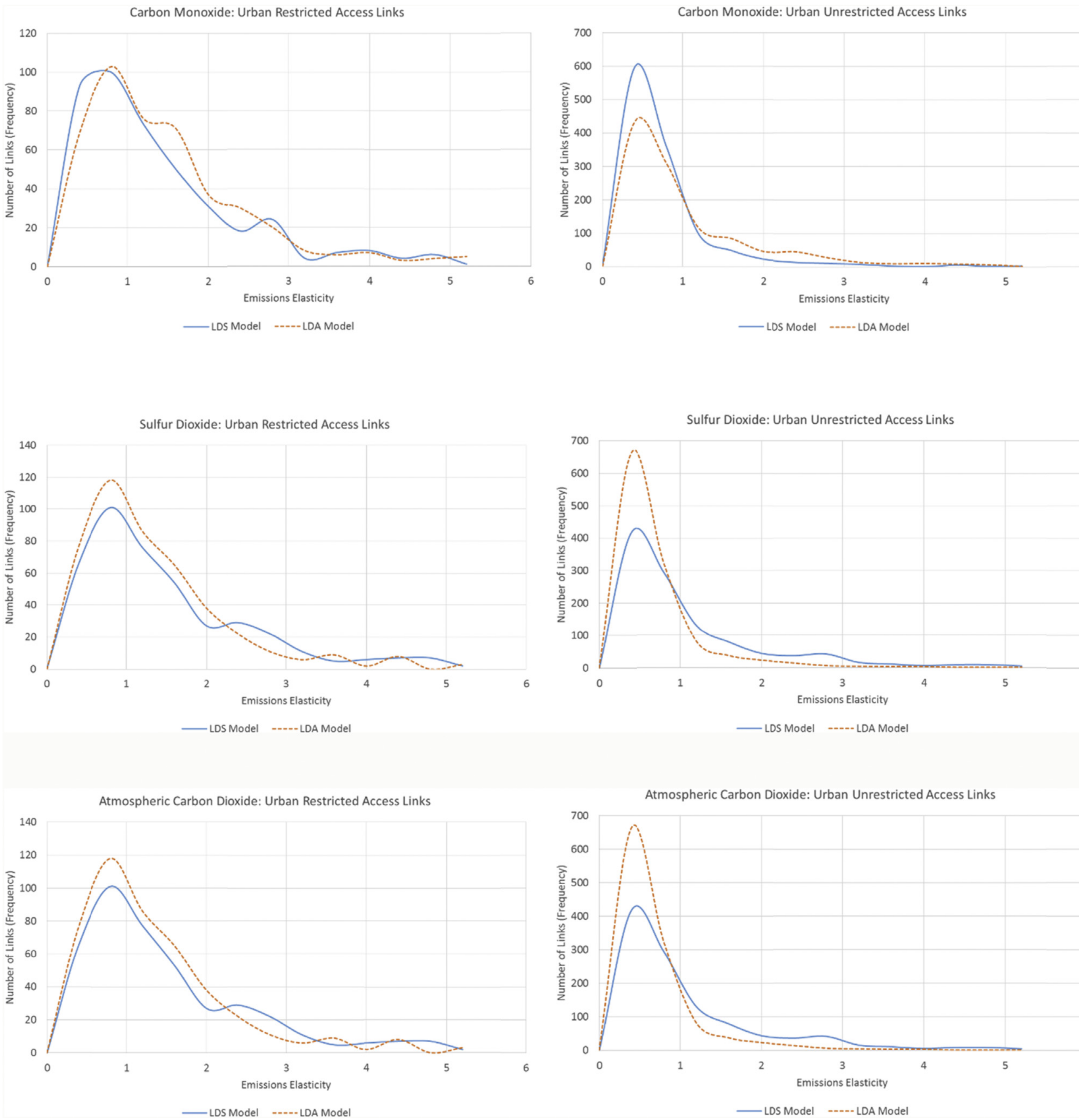

Fig. 7. Distribution of emissions elasticities with link lengths, classified by road-type.

4.3. Emissions variability with road-type classifications

In order to investigate effects of supply-side attributes such as network characteristics, links across the network are classified into categories and emissions are estimated for all individual subsets. First, emission inventories classified by road-type are developed. As defined previously, links are classified into two categories according to their free-flow speeds: urban restricted access and urban unrestricted access. The spatial distributions of emissions over links belonging to either road-type classes are illustrated through the frequency distribution plots in Fig. 5.

As found in the earlier set of distributions for network-wide emissions considering all links in the network, the trends for these two subsets of links are also consistently right-skewed. Consequently, longer left tails (in the high emission estimate regions) are also observed, and again with fatter tails in the LDA model then the LDS model. The mean emission estimates for the LDA model are also higher than the LDS model across both road-type classifications, which is also consistent with the network-wide distributions.

However, for all pollutants modeled, emission trends along the urban restricted access links are relatively more oscillating (or less smooth) than the urban unrestricted access links. Also comparing the distributions for the LDA and LDS models along urban restricted links, the trends are more closely spaced and have similar frequencies, particularly after the peak and until the tail-ends of the curves (or the high-range of emissions). These trends are more prominent for certain criteria pollutants including NO_2, PM10, PM2.5, and SO_2 than the rest. On the other hand, for the urban unrestricted access links, the skewness of plots with respect to each other and deviations in their trends are higher. They are also much similar to the deviations observed in the

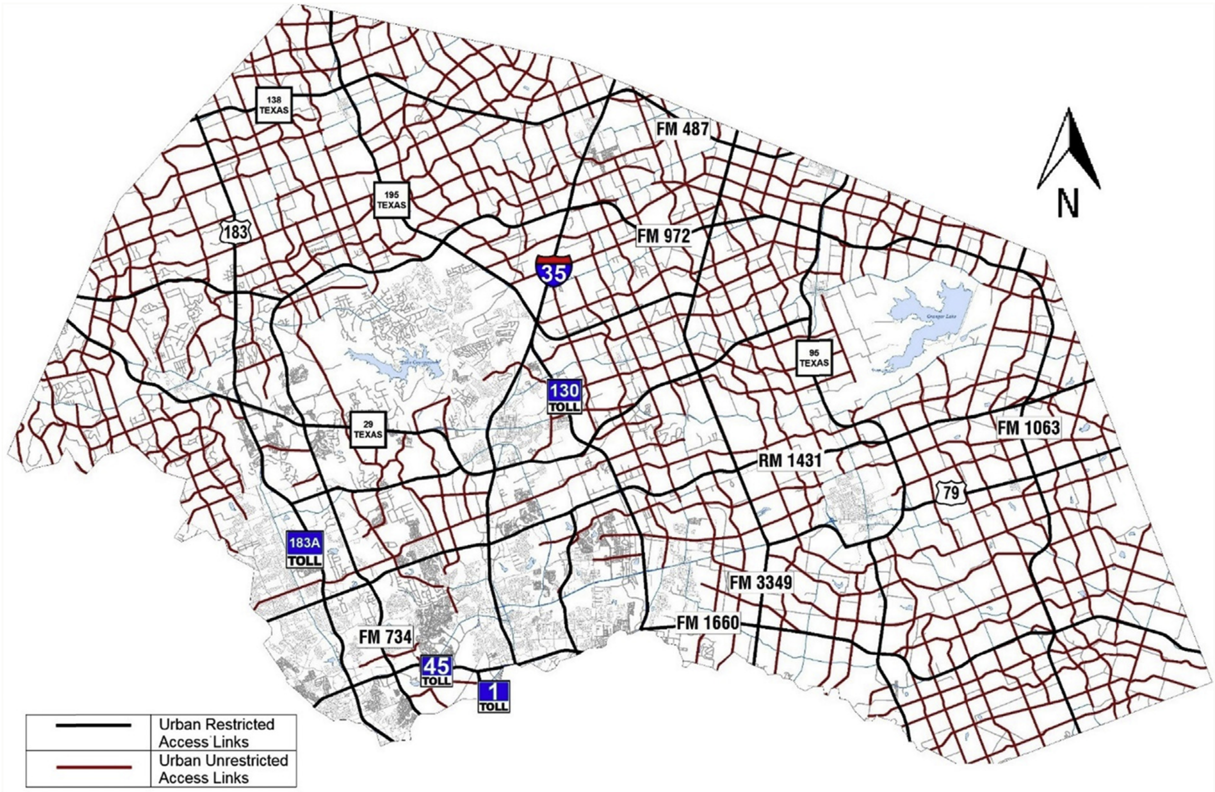

Fig. 8. Study-area network topology.

overall network-wide trends consisting of all the links. Hence, it can be inferred that in this case-study urban unrestricted access links are the major contributors to the deviations in emission estimates across multiple resolutions. Recollect that urban unrestricted access links carry mostly slower speed traffic along local corridors and arterials. These are regions of the network with relatively higher vehicle activity and dynamics considering traffic signals, vehicle stop-starts, intersection controls, and thus more fluctuations in vehicle trajectories and speeds overall. Impacts of congestion in inner cities on local air pollutants was recently also found by Jochem et al. (2016) in a study to evaluate external costs of electric vehicles. The LDS and LDA model inputs and their individual capabilities of capturing this traffic activity, thus, vary much more along these links. This is reflected in more relative skewness of distributions of emission estimates from the respective models.

On the other hand, urban restricted access links carry high-speed traffic such as along freeways that experience relatively lesser traffic dynamics due to lack of intersections or frequently encountered traffic controls. The vehicle trajectories along them are much smoother, and hence the differences in estimates from the LDS and LDA models are not as pronounced. However, it is worth noting that the overall proportion of local unrestricted access links in the network is much lower (28%) than that of the restricted access type (72%), and hence their composition in the overall system capacity is much lower. Despite that, their effects on the network-wide variations in emission estimates are more pronounced. This further underscores the roles of both vehicle dynamics and high resolution traffic data profiles on emissions. It also upholds the merits of the LDS model, in that without its fine-grained emissions utilities, such empirical nuances and sensitivities of emissions could not be easily uncovered.

4.4. Emissions variability with link lengths

The above discussed road-type classifications capture the effects of vehicle activity and speeds. Another physical supply-side attribute, link length, is now chosen. From the above distribution curves, it can be seen that the sensitivities to any explanatory variable more or less follows the same trends across all different pollutants considered. Hence, only a few of these pollutants (particularly the ones with highest sensitivities) are chosen for demonstration. The variability as observed in selected criteria pollutants and GHG is illustrated below.

The scatter plots in Fig. 6 show the variations in emission estimates for a link with its corresponding length, for both the LDS and LDA models. In addition to that, linear regression trend-lines are also fitted over all combinations to investigate the sensitivity or elasticities of emission estimates to changes in link lengths. Link length is, thus, the explanatory or independent variable, and emission estimates are the dependent variables. The regression model expressions and goodness-of-fit (R-squared) values are also shown for all the trend-lines.

As seen in Fig. 6, emissions along urban restricted access links appear to be more responsive to variations in link lengths than those along urban unrestricted access links. As discussed earlier, these links represent high-speed traffic, mostly along freeways and expressways. The links in these corridors are longer and more continuous due to the absence of dense interconnections or intersections, unlike local arterials. High-speed traffic coupled with longer lengths propels the overall traffic flow along these links, and also produces higher VSPs. This is reflected in the more discernible effects of link lengths on emission estimates for CO, SO_2, and atmospheric CO_2 on urban restricted access links, as seen through the wider spread in the scatter plot points. The same insights are conveyed through higher slopes of the regression trend-lines for the urban restricted access links than that of the urban unrestricted access links.

From the regression trend-lines, the effects of varying link lengths on the corresponding emission estimates can also be observed. Sensitivities of emission estimates to link lengths are found to vary across different road-types and emission model resolutions. For CO, the effects of link lengths are found to be more prominent in the LDA model than in the LDS model. However, for the other two pollutants, SO_2 and

atmospheric CO_2, the effects are more or less similar among the two models considering their nearly equal slopes and regression coefficients. Also for the urban unrestricted access links, the LDA model exhibits larger response to link length than the LDS model, but only for SO_2 and atmospheric CO_2. In case of CO, the LDS model is more sensitive to variations in link lengths.

Note that the goodness-of-fit statistics or R-squared values of the regression trend-lines are not very high, ranging between 23% and 27% for urban restricted access links and 13% and 17% for urban unrestricted access links. This indicates a higher incidence of "noise" or variability in the data, as is also visually evident. Several clusters of data points fall further away from the regression line, and there are also many data outliers. These outliers mainly contain links that are a combination of long lengths and high volumes, coupled with high average speeds. All these variables are directly proportional to emission estimates, and thus result in higher magnitudes of link-level emissions. They are also more frequent in urban restricted access links as they are highway and freeway links that are relatively longer and carry higher volumes at faster speeds. Nonetheless, there exist significant trends across the majority of the links, thus indicating that the explanatory variable (link lengths) can still roughly help estimate the dependent variable (emissions). This information is more relevant in the relative sense when comparing the sensitivity or elasticities among different scenarios, such as in the current numerical experiments.

Because emissions over urban restricted access links are more sensitive to link lengths, emission elasticities are explored in further detail. Elasticities convey how link-based emission estimates react to variations in link lengths. Mathematically, emissions elasticity with link lengths is defined as the amount of change in estimates of emissions on a link when there is a one percent change in the corresponding link length. Spatial distributions of elasticities of CO, SO_2, and atmospheric CO_2 emissions across the network are thus developed. Elasticity distributions for the LDA and LDS models are also compared.

As seen in the distribution plots in Fig. 7, emission estimates of SO_2 and atmospheric CO_2 show nearly the same elasticities to link lengths, whereas CO estimates behave much differently. For these three criteria pollutants, high-speed urban restricted access links do not exhibit much differences in distributions of elasticities to link lengths across the LDA and LDS models. As opposed to that, urban unrestricted access links are found to display more variations in elasticities among the LDA and LDS models. This indicates that along low-speed local corridors or arterials, elasticities with link lengths are more influenced by the level of detail considered while modeling traffic activity.

In order to provide a more visual sense of the spatial heterogeneity of the emission results in the study area, the network topology is presented here. It includes the key transportation corridors in the Williamson County region, including major arterials and freeways. The elasticity of emission estimates across the two functional types of links (local unrestricted/restricted access) is evident from the plots in Figs. 6 and 7 and can be put in better spatial perspective using Fig. 8 (Williamson County Long-Range Transportation Plan, 2016).

5. Conclusions

This section summarizes the current study, with an overview of the modeling features covered, and key contributions of the current study. Major findings regarding supply-side dependencies of emission estimates as unearthed from the numerical application in Williamson County, Texas are covered. Certain practical limitations and future research avenues are also discussed.

5.1. Summary of study

Impelled by the relevance of mobile-source emissions for policy and regulatory purposes, the current study develops a modeling framework that integrates the MOVES emissions package with a mesoscopic simulation-based DTA engine. It captures a wider range of sensitivities of emission estimates, and broadens the understanding of supply-side network elements that play a role in estimating emissions from the region. These tools can also be useful in long-range urban transportation planning and environmental impact assessment. Some unique analytical features of the study include inclusion of dynamic factors of traffic into the emissions modeling process using per-second vehicle trajectories, and investigation of emission estimates at multiple resolutions and granularity of vehicle activity. The proposed model links demand-side vehicle activity with network-based emissions at fine spatial and temporal resolutions. The LDA and LDS models also provide policy insights in terms of computational challenges that agencies may face in collecting and managing such fine-grained data for applications, and the modeling decisions made to overcome them.

5.2. Key findings and policy implications

In the practical context, selection of either modeling resolutions has both environmental and analytical implications. These are uncovered through numerical experiments on the Williamson County study-area, by developing link-level emissions inventories for some key criteria pollutants (CO; NO_2; coarse PM10; fine PM2.5; and SO_2) and GHG (CO_2) for a morning weekday peak hour. The coarser LDA model containing hourly data averages projects higher median emission estimates across the network than that of the fine-grained LDS model containing per-second link data. Modeled emission estimates are also found to be sensitive to various supply-side attributes such as road-type classifications of links, their speeds, and lengths. Further analysis is done in this regard using a trend-line regression approach. The sensitivity is found to vary by road-type classes of links, in that emissions from urban restricted access links catering to high-speed traffic are found to be more influenced by link lengths.

In terms of effects across different modeling resolutions (LDS and LDA), however, different trends are observed. Urban unrestricted access links, which carry traffic along local corridors or arterials, are found to contribute more to variations in estimates from the LDS and LDA models. This is mainly attributed to the fact that local corridors more commonly witness vehicle activity fluctuations and alternating operating modes, leading to more irregular vehicle trajectories. These are captured differently by the LDS and LDA models. The current analysis, thus, opens the doors to deeper understanding of the behavior of fine-grained emissions by leveraging dynamic traffic models. At the same time, it presents workable tools for planning and regulatory purposes.

Network-based emissions are very commonly employed in research and practice, and hence their sensitivities across supply-side network attributes and choice of traffic data can have policy and regulatory implications. For instance, fast-developing areas with higher degree of traffic activity or complex distributions of roadway networks are more likely to exhibit greater emissions variance (both spatially and quantitatively), and thus more challenges in accurately estimating them at a regional-level. These estimates are among the most critical bits of information taken into consideration during environmental conformity assessment of areas, which determines their eligibility for procurement and government funding of large-scale transportation and mobility projects across the region.

5.3. Study limitations and future work

While the current study expands the literature of network-based traffic emissions, there are certain practical limitations that must be also recognized. The LDA and LDS models capture vehicle activity at hourly and per-second time intervals, respectively, but there is another finer degree possible—operating mode distributions. Currently, based on the drive schedules provided by the mesoscopic SB-DTA engine, default MOVES operating mode distributions are used as discussed earlier. However, if available, they can also be user-supplied where the

traffic model can be used to provide the distribution of per-second vehicle operating modes (acceleration, deceleration, idling, braking, etc.). Given the extreme fine resolution of these data, obtaining and managing these is practically cumbersome. From the point of view of meaningful application, they become computationally almost infeasible, if not impossible for a study area with network-sizes of more than a handful of links. Developing a realistic snapshot of the environmental impacts of traffic often involves encountering region-wide areas. These are commonly represented by planning-level networks containing a mix of freeway and local links, such as the Williamson County network considered in this study (which contains more than 1600 links belonging to different classes, and covers nearly a thousand square-mile geographical area). Hence, customized operating mode distributions offer very limited applicability to any realistic planning-level area. A limited number of prior microsimulation-based studies have considered their application, but only to relatively localized areas or test-beds such as a section of a limited access highway that included eleven links (Abou-Senna et al., 2013). Nevertheless, such fine-grained emissions capabilities can serve vital purposes in corridor-level emissions modeling, PM hot-spot analyses, and even dispersion modeling. But in order to leverage them for planning and regulatory procedures, their deployment must be expanded to the system level to provide network-wide emissions inventories. It must also be pointed out that while links can be segregated based on functional type and lengths whereby they account for the variables of vehicle speed and acceleration, they can be further split by other criteria that could capture additional supply-side features. The study-area in this study is a suburban county where there are not much further supply-side network variations other than the ones already considered here.

Potential future extensions to the current models thus include development of a new range of modeling tools, with new assumptions and simplifying methods that may enable deployment of custom per-second operating mode distributions. This could further add a degree of rigor beyond the LDA and LDS models to dynamic mobile-source emissions estimation. Also from the supply-side standpoint, apart from the variables considered in the current study, several others such as the number of traffic lights/mile, roadway design, street-parking, pavement quality, etc. have not been considered and are worth exploring in the future. The research literature in this domain is fast evolving, but dynamic factors such as traffic and congestion-based variables continue to pose challenges in accurate and realistic emissions estimation. They also depend on the nuances of the area being investigated. At the same time, the vehicle fleet worldwide is radically changing with the advent of new vehicle technologies such as hybrid or electric vehicles, and even self-driving autonomous vehicles. They bring along their own unique research challenges in fully assessing their far-reaching environmental impacts and the associated policies.

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